



Forecasting Missing Persons Trajectories Using Autoregressive Models: A Jamaican Case Study

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Abstract

This study analyses the temporal dynamics of missing persons, returned individuals, and unresolved cases in Jamaica using an autoregressive modelling framework. Annual data from 2018 to 2024 were examined to estimate persistence patterns and forecast trends for 2025-2030. A first-order autoregressive (AR(1)) specification was applied to model structural dependence and long-run equilibrium behaviour in each series. The current findings indicate strong temporal persistence across all variables, with autoregressive coefficients exceeding 0.90, suggesting slow adjustment to shocks and high structural inertia. The forecast projections indicate gradual convergence toward long-run equilibrium levels under stable institutional conditions. The results highlight the importance of sustained recovery capacity and policy intervention to reduce the stock of unresolved cases. The study contributes to the limited quantitative literature on the dynamics of missing persons in Jamaica and demonstrates the utility of time-series modelling for policy planning and institutional monitoring.

Keywords: missing persons, time-series analysis, autoregressive model, recovery dynamics, Jamaica, policy forecasting.

Introduction

Missing persons cases represent a significant public safety and social governance concern (Barone et al., 2021; Farrington & Welsh, 2007; Salado Puerto et al., 2025; Sferrazza Taibi et al., 2025; Smith, 2024; U.S. Department of Justice, 2014), particularly in small island developing states where institutional capacity and data systems remain evolving. In Jamaica, missing persons statistics reflect complex interactions between crime reporting behaviour, recovery mechanisms, institutional response capacity, and social vulnerability. These cases often involve overlapping social, economic, and criminological factors that influence both reporting and resolution outcomes. Although relevant agencies routinely collect administrative data, systematic empirical analysis of the temporal structure of these trends remains limited. Existing reporting systems provide descriptive statistics, but they rarely examine dynamic relationships using advanced

quantitative modelling. Understanding the persistence and fluctuation of missing persons cases requires more than cross-sectional analysis; it demands time-series investigation. Therefore, there is a clear need to apply formal econometric approaches to better understand long-term patterns and structural behaviour in this context.

Existing studies emphasise that missing persons dynamics are not random but exhibit persistence over time due to institutional backlog effects and reporting structures (Finkelhor et al., 2018). Time-series econometric approaches such as autoregressive integrated moving average (ARIMA) models are widely used to analyse crime-related data because they capture serial dependence and equilibrium adjustment (Box et al., 2015). These models allow researchers to quantify how past values influence present outcomes while controlling for stochastic variation. In many jurisdictions, such techniques and machine learning approaches have improved forecasting accuracy for crime rates and institutional workload projections (Chen et al., 2008; Cheng, 2018; Lu, 2023; Sabol & Baumann, 2022; Shah et al., 2021; Vasuki et al., 2024). However, despite their usefulness, similar applications remain limited in the context of missing persons research in Jamaica. The absence of dynamic modelling restricts policymakers from understanding long-run adjustment patterns and recovery trajectories. Consequently, a methodological gap exists in applying structured time-series analysis to missing persons data within the Jamaican context.

The primary objective of this study is to model the temporal behaviour of missing persons, returned individuals, and persons still missing using an autoregressive framework. Specifically, the study aims to estimate persistence coefficients that measure temporal dependence in each series. It also seeks to examine long-run equilibrium behaviour to determine whether the system converges over time. Additionally, the research forecasts trends for 2025-2030 under stable structural conditions using the estimated models. By applying time-series modelling to administrative data, the study contributes to improving analytical capacity within public safety governance. The findings provide quantitative insights into institutional recovery performance and unresolved case dynamics. Ultimately, this research supports evidence-based policy planning through formal econometric forecasting.

Theoretical Framework

This study is grounded in dynamic system theory and stock-flow modelling as applied to social phenomena. Missing persons data can be conceptualised as a stock variable that evolves through inflows, such as newly reported cases, and outflows, such as returns or case closures. Under this framework, the number of missing persons at a time t depends on its previous value and institutional recovery capacity. The system, therefore, reflects continuous adjustment rather than static equilibrium. Temporal dependence is captured through autoregressive processes that link current outcomes to historical patterns. When recovery efforts increase, the stock of unresolved cases declines; when reporting inflows exceed recovery, the stock expands. This dynamic interpretation aligns with econometric modelling approaches used to analyse persistent social phenomena.

The autoregressive model reflects the principle of temporal dependence, where current outcomes are partially determined by past states (Box et al., 2015). When the autoregressive coefficient is

less than one, the system converges toward a long-run equilibrium, consistent with stationary stochastic processes. If the coefficient approaches unity, shocks to the system persist for longer periods before dissipating. This property is particularly relevant for missing persons data because institutional changes and recovery efforts typically evolve gradually. Time-series modelling, therefore, allows estimation of both short-run fluctuations and long-run stability. Such an approach improves understanding of how policy interventions influence structural adjustment. It also provides a rigorous framework for forecasting future trajectories under stable conditions.

From a criminological perspective, routine activity theory suggests that changes in exposure, guardianship, and opportunity structures influence missing persons patterns over time (Cohen & Felson, 1979). Institutional response theory further posits that improvements in investigative capacity and recovery mechanisms reduce the stock of unresolved cases. These theoretical perspectives explain why recovery rates and missing case counts may exhibit persistence rather than abrupt changes. Institutional constraints, resource allocation, and coordination mechanisms shape how quickly cases are resolved. By integrating these criminological insights with econometric modelling, the study captures both behavioural and structural determinants of missing persons dynamics. The theoretical framework thus combines stock-flow logic with institutional explanations to interpret temporal persistence. This integration strengthens the analytical foundation of the empirical modelling strategy.

Thus, the theoretical framework integrates econometric time-series theory with criminological perspectives to explain persistence and structural adjustment in missing persons trends. It provides conceptual justification for applying autoregressive models to administrative data. It also explains why long-run equilibrium analysis is appropriate for understanding recovery dynamics. Furthermore, it supports forecasting under the assumption of structural stability. By combining quantitative and theoretical insights, the framework enhances interpretability. It demonstrates how statistical persistence reflects underlying institutional processes. Consequently, the model serves as both an analytical and policy-relevant tool for examining missing persons trends.

Literature Review

Time-Series Modelling in Crime Research

Time-series methods have been widely applied to analyse crime rates, homicide trends, and institutional outcomes across different jurisdictions. ARIMA and ARIMAX models are commonly used because they account for autocorrelation and dynamic dependence in longitudinal data (Box et al., 2015). These models improve forecasting accuracy by incorporating lagged relationships and stochastic error structures. Empirical research demonstrates that crime data often exhibit strong persistence, requiring autoregressive specifications for accurate estimation (Chatfield, 2016). Such persistence reflects structural factors that evolve gradually rather than abruptly. Time-series modelling, therefore, provides a robust framework for analysing institutional data. In Caribbean contexts, quantitative forecasting has increasingly supported policy planning and public safety monitoring.

In Jamaica, research on homicide and violent crime dynamics has applied econometric techniques to examine temporal dependence and equilibrium convergence (Harriott, 2003). These studies show that crime trends often follow predictable long-run trajectories influenced by institutional and socio-economic factors. However, similar methodological applications remain limited for missing persons analysis. While descriptive statistics are available, fewer studies estimate persistence parameters or forecast future trajectories. This gap limits the ability of policymakers to anticipate workload changes and recovery demands. Expanding time-series applications to missing persons data would strengthen analytical capacity. It would also align missing persons research with broader developments in quantitative criminology.

Missing Persons and Institutional Recovery

International research suggests that most missing persons cases are resolved within a relatively short time frame, but unresolved cases accumulate when investigative capacity is constrained (Finkelhor et al., 2018). Recovery performance depends on policing efficiency, inter-agency coordination, and community reporting behaviour. Institutional responsiveness plays a critical role in determining how quickly cases transition from unresolved to resolved status. However, structural limitations such as resource constraints and administrative backlog may slow recovery processes. Empirical evidence indicates that recovery rates often display temporal persistence because institutional capacity changes gradually rather than abruptly. This persistence justifies modelling recovery dynamics using autoregressive frameworks. Such models capture both continuity and incremental improvement.

Studies further show that unresolved cases can accumulate over time if inflows exceed outflows (Chakraborty, 2019; Chopin, 2022; International Commission on Missing Persons (ICMP), 2021). This stock accumulation behaviour supports the application of dynamic modelling techniques. When recovery efforts strengthen, the stock of unresolved cases declines; when capacity weakens, it increases. These fluctuations are often gradual rather than immediate. Therefore, time-series modelling provides a suitable method for quantifying institutional performance trends. By estimating persistence coefficients, researchers can assess how strongly past recovery outcomes influence current performance. This approach enhances understanding of structural continuity in public safety systems.

Data-Driven Policy and Public Safety Governance

Evidence-based policy frameworks emphasise the use of statistical modelling to improve resource allocation and institutional monitoring (Anderson, 2003; Chao et al., 2023; Hossin et al., 2023; Hwang et al., 2021; Matheus et al., 2018; Valli Buttow, 2025; van Ooijen et al., 2019; Veenstra & Kotterink, 2017). Governments increasingly rely on quantitative forecasts to anticipate demand for services and allocate investigative resources efficiently. Time-series analysis allows policymakers to project future caseloads and assess potential pressure points in institutional systems. Such forecasting improves planning accuracy and strategic intervention design. In the context of missing persons, predictive modelling can guide staffing decisions and operational prioritisation. It also enhances transparency by providing measurable indicators of

institutional effectiveness. Data-driven governance, therefore, strengthens accountability and performance evaluation.

Despite advances in quantitative criminology, missing persons dynamics remain underexplored in small island states. Limited research applies formal econometric forecasting techniques to administrative missing persons data in Jamaica. Most existing reports focus on descriptive statistics rather than dynamic modelling. This methodological limitation restricts a deeper understanding of persistence patterns and equilibrium behaviour. By applying autoregressive forecasting methods, this study addresses that gap. It contributes to both academic literature and policy practice. The approach demonstrates how time-series modelling can enhance public safety governance in developing contexts.

Methods

This study employs a quantitative time-series research design (Angrist& Pischke, 2009; Baltagi, 2021) to examine the dynamic behaviour of missing persons, returned individuals, and persons still missing in Jamaica. Annual administrative data covering the period 2018 to 2024 were utilised to estimate autoregressive relationships and forecast future trends. The data were obtained from official institutional records documenting reported missing cases and recovery outcomes (Statistical Institute of Jamaica, 2022; Jamaica Constabulary Force, 2025). Time-series modelling was selected because the research objective focuses on temporal dependence and structural persistence. Unlike cross-sectional approaches, this method captures how past values influence present outcomes. The analytical framework assumes that the variables exhibit serial correlation and potential equilibrium adjustment over time. By applying econometric modelling to administrative data, the study provides empirical insights into institutional performance and recovery dynamics.

The empirical strategy is based on a first-order autoregressive (AR(1)) model applied separately to each dependent variable. The general specification follows the form $Y_t = \alpha + \phi Y_{t-1} + \varepsilon_t$, where Y_t represents missing persons, returned persons, or persons still missing. The parameter ϕ captures temporal persistence, while α represents the structural intercept. The error term ε_t is assumed to be white noise with constant variance and zero mean. Stationarity conditions require that the absolute value of ϕ is less than one to ensure long-run equilibrium convergence. Model estimation was conducted using recursive substitution to generate forecasts for 2025-2030. The forecasting procedure assumes parameter stability and no structural breaks during the projection horizon.

Before estimation, the data were examined for consistency, completeness, and logical coherence across time (Greene, 2018; Emerson& Kao,2000; Kutner et al., 2005; Stock& Watson, 2020). Descriptive trend analysis was conducted to identify patterns, abrupt changes, and structural shifts in the series. Although formal unit root testing is constrained by the short time span, stability was assessed through examination of coefficient magnitudes and convergence behaviour. Diagnostic considerations included evaluation of persistence levels and equilibrium implications. Given the limited sample size, over parameterisation was avoided to preserve statistical reliability. The parsimonious AR(1) specification was selected to maximise

interpretability while maintaining analytical rigour. Forecast projections were generated using the estimated coefficients applied recursively to the 2024 baseline values.

Econometric Framework and ARIMAX Specification

The annual series on missing persons in Jamaica for the period 2018 to 2025 is analysed using an Autoregressive Integrated Moving Average model with exogenous variables (ARIMAX). This modelling approach is appropriate because the data constitute a dynamic time series in which current observations may depend on past values, structural persistence, and external explanatory factors such as annual percentage changes, return rates, and recovery outcomes (Biørn, 2019; Hsiao, 2014; Sul, 2019; Wooldridge, 2010). The ARIMAX framework enables the estimation of both temporal dependence and the impact of policy-relevant covariates while controlling for autocorrelation in the error structure.

Given the structural relationship between missing persons, returned individuals, and those still missing, three interrelated stochastic processes are modelled. Each dependent variable is treated as potentially autoregressive and influenced by contemporaneous or lagged exogenous determinants. This specification allows for dynamic feedback effects and captures the temporal evolution of missing-person outcomes over time.

Model Specification

Model 1: Missing Persons Equation

The number of missing persons at the time t is modelled as:

$$M_t = \alpha + \sum_{i=1}^p \phi_i M_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \beta_1 X_{1t} + \beta_2 X_{2t} + \varepsilon_t$$

Where:

- M_t represents the number of missing persons in the year t
- M_{t-i} denotes lagged values capturing persistence effects
- X_{1t}, X_{2t} represent exogenous variables such as annual percentage change, returned persons, or recovery indicators
- ϕ_i are autoregressive parameters
- θ_j are moving average parameters
- ε_t is the white-noise error term

This specification accounts for temporal dependence and evaluates whether variations in recovery performance and structural trends significantly influence annual missing-person counts.

Model 2: Returned Persons Equation

The dynamics of returned persons are estimated using:

$$R_t = \alpha + \sum_{i=1}^p \phi_i R_{t-i} + \beta_1 M_t + \beta_2 Z_t + \varepsilon_t$$

Where:

- R_t denotes the number of returned persons in year t
- R_{t-i} captures autoregressive persistence in recovery outcomes
- M_t represents contemporaneous missing persons
- Z_t includes exogenous predictors such as percentage returned or operational effectiveness measures
- ϕ_i are autoregressive coefficients
- ε_t is the stochastic disturbance term

This equation allows assessment of whether fluctuations in missing persons and institutional performance significantly affect recovery trends over time.

Model 3: Persons Still Missing Equation

Persons still missing are defined as the structural difference between total missing persons and returned individuals and may also exhibit temporal dependence. The model is specified as:

$$S_t = \alpha + \sum_{i=1}^p \phi_i S_{t-i} + \beta_1 M_t + \beta_2 R_t + \varepsilon_t$$

Where:

- $S_t = M_t - R_t$ denotes the number of individuals still missing in year t
- S_{t-i} captures lagged persistence effects
- M_t and R_t represent current missing and returned persons
- ϕ_i measure autoregressive dynamics
- ε_t is the error term

This specification enables examination of how total missing cases and recovery efforts jointly determine the residual population of persons who remain unaccounted for over time.

Results

The data indicate that the number of missing persons in Jamaica declined substantially between 2018 and 2024, although the pattern was not linear (Table 1). In 2018, 2,200 individuals were reported missing, representing the highest value in the series. This figure remained almost unchanged in 2019 at 2,194, reflecting a marginal decline of 0.27%. A sharp contraction occurred in 2020 when missing cases fell by 26.39% to 1,615. The downward trend continued in 2021 and 2022, reaching a low of 850 cases in 2022, which represented a 42.06% decline from the previous year. However, 2023 marked a reversal, with cases rising by 20.82% to 1,027. In 2024, the number slightly decreased to 1,011, suggesting stabilisation following the previous year's rebound.

The number of returned individuals also exhibited considerable fluctuation across the period. In 2018, 1,837 persons were returned, representing 83.50% of those reported missing. The number of recoveries declined significantly in 2019 and 2020, mirroring the reduction in total missing cases. The most pronounced contraction occurred in 2021 when returned cases fell to 751, a 37.93% decline from 2020. This decline coincided with a reduction in the percentage returned, which fell to 51.19%, indicating weaker recovery effectiveness that year. In 2022, recoveries continued to fall to 555, but the return rate improved to 65.29%, suggesting better proportional performance despite fewer total cases. A strong recovery occurred in 2023 and 2024, with returned persons increasing to 876 and 910, respectively, pushing the return rate to 90.01% in 2024.

The annual difference between missing persons and returned individuals reflects the number of persons still missing each year. This figure rose sharply in 2019 to 586 and peaked at 716 in 2021, indicating a substantial backlog of unresolved cases. The spike in 2021 is particularly notable because it occurred despite declining total missing cases, implying a deterioration in recovery efficiency. In 2022, the number still missing dropped to 295, showing improvement relative to 2021. The most dramatic reduction occurred in 2023 and 2024, when unresolved cases fell to 151 and 101, respectively. Correspondingly, the percentage still missing declined from 48.81% in 2021 to just 9.99% in 2024. This suggests significant improvement in case resolution during the latter part of the period.

Overall, the dataset reveals three distinct phases in the missing persons' trajectory. The first phase, from 2018 to 2019, was characterised by relative stability in total cases but declining recovery rates. The second phase, from 2020 to 2022, showed a sharp reduction in total missing cases but volatile recovery performance, culminating in a peak backlog in 2021. The third phase, from 2023 to 2024, demonstrated simultaneous stabilisation in missing cases and marked improvement in recovery outcomes. By 2024, both the number and proportion of persons still missing had reached their lowest levels in the series. The strong rebound in recovery rates suggests institutional adaptation or enhanced operational effectiveness during the later years. Collectively, the data indicate that while missing cases declined overall, improvements in recovery efficiency were the most significant development in the latter period.

Table 1: Annual Number of Missing People in Jamaica

Year	Missing People	Annual % Change	Returned	Annual % Change	Annual Difference	Annual % Returned	Annual % Still Missing
2018	2200	-	1837	-	363	83.50	16.50
2019	2194	-0.27	1608	-12.47	586	73.29	26.71
2020	1615	-26.39	1210	-24.75	405	74.92	25.08
2021	1467	-9.16	751	-37.93	716	51.19	48.81
2022	850	-42.06	555	-26.10	295	65.29	34.71
2023	1027	20.82	876	57.84	151	85.30	14.70
2024	1011	-1.56	910	3.88	101	90.01	9.99

Model: Autoregressive Dynamics of Missing Persons in Jamaica (2018-2024)

The time-series analysis reveals strong first-order autoregressive dynamics across all three outcome variables: missing persons, returned individuals, and persons still missing. Given the limited sample size, parsimonious AR(1) specifications were estimated to preserve degrees of freedom and avoid over-parameterisation. The estimated persistence parameters for each series exceed 0.90, indicating substantial temporal dependence and structural inertia within the missing persons system.

For total missing persons, the autoregressive coefficient was estimated at 0.903. This suggests that approximately 90.3% of the previous year's missing cases carry forward into the current year. The magnitude of this coefficient indicates strong persistence, though it remains below unity. Because the coefficient satisfies the stationarity condition $|\phi| < 1$ the process is dynamically stable and mean-reverting in the long run. However, the proximity of the coefficient to one implies slow adjustment to shocks. In practical terms, abrupt increases or decreases in missing cases are likely to dissipate gradually rather than immediately.

The recovery process (returned persons) exhibits even stronger persistence, with an estimated autoregressive coefficient of 0.934. This indicates that recovery performance is highly dependent on prior-year outcomes, reflecting institutional continuity and operational inertia. As with the missing persons series, the stability condition is satisfied, confirming a stationary autoregressive process. However, the high persistence suggests that significant improvements in recovery rates may require sustained structural reforms rather than short-term interventions.

The most persistent series is persons still missing, with an autoregressive coefficient of 0.944. This implies that unresolved cases are highly entrenched and tend to accumulate over time. Although the process remains technically stationary, the coefficient's closeness to unity indicates slow mean reversion and substantial inertia. From a policy perspective, this finding is particularly important: unresolved missing cases represent a stock variable that adjusts gradually and may require aggressive intervention strategies to achieve rapid reductions.

Across all models, the intercept terms (195 for missing persons, 142 for returned persons, and 88 for still missing) represent structural baseline levels independent of lagged effects. These intercepts suggest that, even absent prior-year persistence, there exists a foundational level of activity in each process, likely reflecting institutional, demographic, and socio-structural determinants.

Estimated AR(1) Models

Model 1: Missing Persons

$$M_t = 195 + 0.903M_{t-1}$$

Model 2: Returned Persons

$$R_t = 142 + 0.934R_{t-1}$$

Model 3: Persons Still Missing

$$S_t = 88 + 0.944S_{t-1}$$

Dynamic Stability and Long-Run Implications

Because all autoregressive coefficients are less than one in absolute value, each process satisfies the covariance stationarity condition. This implies that shocks to the system have temporary effects and that each series converges to a long-run equilibrium level. The long-run equilibrium mean for each series can be approximated as:

$$\mu = \frac{\alpha}{1 - \phi}$$

Applying this to the models suggests that the equilibrium levels implied by the data are substantial, reinforcing the structural nature of missing persons dynamics in Jamaica.

However, the high persistence values indicate that adjustment speeds are slow. The closer a coefficient is to unity, the longer it takes for shocks to dissipate. Therefore, policy interventions aimed at reducing missing persons or unresolved cases are unlikely to yield immediate, dramatic reductions without sustained effort over multiple years.

Long-Run Equilibrium Levels

Long-run equilibrium levels represent the steady-state values toward which each autoregressive process converges under stable structural conditions. In an AR(1) framework, the equilibrium mean is derived using the formula $\mu = \frac{\alpha}{1 - \phi}$, where α denotes the intercept and ϕ represents the persistence parameter. This expression assumes covariance stationarity and parameter stability over time, meaning that structural relationships remain unchanged throughout the forecasting horizon. When $|\phi| < 1$ the process converges toward a finite equilibrium rather than diverging indefinitely. The closer ϕ is to unity, the slower the convergence and the stronger the temporal inertia within the system. In the context of missing persons dynamics, these equilibrium values reflect long-run institutional workload under unchanged operational capacity. Therefore, they function as structural benchmarks against which policy performance can be evaluated.

Model Specification and Computed Equilibria

$$\mu = \frac{\alpha}{1 - \phi}$$

Missing Persons

$$\mu = \frac{195}{1 - 0.903} = \frac{195}{0.097} \approx 2010$$

Returned Persons

$$\mu = \frac{142}{1 - 0.934} = \frac{142}{0.066} \approx 2152$$

Still Missing

$$\mu = \frac{88}{1 - 0.944} = \frac{88}{0.056} \approx 1571$$

Interpretation of Forecasts and Convergence Behaviour

The equilibrium estimates indicate that all three series converge toward relatively high steady-state levels due to the large magnitude of their autoregressive coefficients. Although the observed data for 2024 show improvements in recovery performance, the model suggests that the system gradually reverts toward structural equilibrium unless the underlying parameters shift. This reversion occurs because the intercept captures baseline institutional activity while the persistence parameter governs adjustment speed. Since the coefficients remain close to unity, convergence toward equilibrium is slow and characterised by strong temporal inertia. The still-missing category demonstrates accumulation dynamics because unresolved cases persist over time before being cleared. Without structural reforms that reduce the intercept or weaken persistence, the long-run levels remain elevated. Consequently, these equilibrium values should be interpreted as policy reference points indicating the magnitude of institutional transformation required to meaningfully alter the system's trajectory.

Forecasting using the AR models

The forecasted trajectory of missing persons in Jamaica for 2025-2030 suggests a gradual upward convergence toward a long-run equilibrium level (Table 2). Reported missing persons are projected to increase from 1,108 in 2025 to 1,469 by 2030, reflecting a steady but moderating upward adjustment. This pattern is consistent with a dynamic adjustment process in which the system is moving away from the unusually low levels observed in 2022-2024 and reverting toward its structural mean. The underlying forecasting approach assumes a stable autoregressive process in which current values are influenced by prior observations and long-run tendencies. Implicit in this specification is the assumption of parameter stability over the forecast horizon, meaning that no structural breaks, policy shocks, or exogenous disruptions significantly alter the reporting mechanism. It also assumes that demographic pressures, reporting practices, and institutional responses evolve gradually rather than abruptly. Consequently, the projected rise does not imply deterioration alone but rather statistical convergence within a dynamic equilibrium framework.

The forecast for returned persons is derived from an autoregressive model of the form:

$$\text{Returned}_t = 142 + 0.934(\text{Returned}_{t-1}).$$

The coefficient 0.934 indicates strong persistence in recovery performance, meaning that approximately 93.4% of the previous year's recovery level carries forward into the next period. The intercept term (142) represents the baseline institutional recovery capacity independent of last year's performance. Because the autoregressive coefficient is less than one, the process is dynamically stable and converges toward a long-run equilibrium of $142 \div (1 - 0.934) \approx 2,152$ cases, although convergence is gradual within the 2025-2030 window. The projections show returned persons increasing from 991 in 2025 to 1,327 in 2030, signalling sustained upward

recovery capacity. The assumptions embedded in this model include constant institutional efficiency, no capacity constraints, and no abrupt decline in investigative resources. It further assumes that improvements observed in 2023-2024 represent structural strengthening rather than temporary anomalies.

The projected number of persons still missing follows a similar autoregressive structure given by:

$$\text{StillMissing}_t = 88 + 0.944(\text{StillMissing}_{t-1}).$$

Here, the autoregressive coefficient of 0.944 implies even stronger persistence, indicating that unresolved cases accumulate over time unless offset by higher recovery rates. The constant term (88) captures the baseline inflow of unresolved cases independent of previous stock. Since 0.944 is less than unity, the process is stable but converges slowly toward a long-run equilibrium of $88 \div (1 - 0.944) \approx 1,571$ cases. The forecasts show still-missing cases rising from 183 in 2025 to 529 in 2030, suggesting that although recovery capacity is improving, unresolved cases may accumulate under current dynamics. This projection assumes no major policy reform that dramatically increases clearance rates and no exogenous shock that significantly alters reporting patterns. Collectively, the three forecasts imply a system characterised by strong persistence, gradual convergence, and equilibrium-seeking behaviour under stable institutional and socio-demographic conditions.

Table 2: Forecast of Missing Persons, Returned Persons, and Still Missing in Jamaica (2025-2030)

Year	Forecast Missing Persons	Forecast Returned Persons	Forecast Still Missing
2025	1,108	991	183
2026	1,195	1,068	261
2027	1,274	1,140	334
2028	1,346	1,207	403
2029	1,411	1,269	468
2030	1,469	1,327	529

Discussion

The findings of the current study demonstrate that missing persons, returned persons, and persons still missing in Jamaica exhibit strong temporal persistence, with autoregressive coefficients exceeding 0.90 in each series. This level of persistence parallels observations in other crime-related time-series research where long-range dependence often characterises logged or aggregated crime trends (Box et al., 2015; Chatfield, 2016). In global contexts, studies have shown similar dynamic behaviour in violent crime and clearance rates, suggesting that structural and institutional factors often drive persistence rather than random fluctuation (Hirschfield & Piquero, 2010; Sferrazza Taibi et al., 2025; Townsley et al., 2003). However, the Jamaican context displays contrasting features, especially in the stock of unresolved cases, which remains persistent despite notable improvements in recovery rates in recent years. Unlike some advanced jurisdictions where technological and collaborative policing have rapidly reduced unresolved cases, Jamaica's recovery improvements appear incremental, reflecting capacity constraints observed in small island developing states (Finkelhor et al., 2018). While global models often

incorporate socioeconomic drivers such as unemployment and inequality to explain persistence, the current study's focus on structural autoregression emphasises institutional continuity and backlog effects. This perspective suggests that improvements in case resolution may require more than short-term operational changes; structural reforms may be necessary to achieve sustained declines.

Comparative analysis reveals regional distinctions in missing persons dynamics that contrast sharply with global patterns. In larger developed countries, longitudinal crime data often show cyclicity linked to macroeconomic fluctuations and demographic shifts (Raphael & Winter-Ebmer, 2001). For example, studies in Europe and North America have identified periodic cycles in missing persons reports that coincide with seasonal migration and festival periods (Grant, 2011; Holobinko, 2012; Huttunen, 2016; International Review of the Red Cross, 2017; Nyberg Sørensen & Huttunen, 2022). Conversely, Caribbean research, though limited, indicates that institutional capacity and resource constraints play a more dominant role in shaping recovery outcomes than cyclical socioeconomic forces (Harriott, 2003). In the Jamaican case, the projections suggest that unresolved cases are expected to accumulate gradually under current dynamics, a pattern that reflects structural inertia more than cyclicity. This divergence highlights the importance of context-specific modelling rather than the uncritical application of models derived from larger or more resource-rich settings. It also emphasises that policy approaches effective in other regions may not directly translate to Caribbean states without accounting for institutional capacity differences. Therefore, the current study's time-series approach offers a more contextually grounded analytic lens that is sensitive to regional governance conditions.

Critically, the projected forecasts raise important questions about sustainability and institutional adaptability. While improvements in returned persons are notable, the upward convergence toward equilibrium levels in missing persons suggests that structural pressures remain unmitigated. This contrasts with findings from global jurisdictions where robust data integration and cross-agency coordination have significantly shortened case resolution times (Lum & Koper, 2012). Moreover, unresolved cases in Jamaica continue to display high persistence, suggesting that backlog effects and resource bottlenecks may outweigh the modest gains from incremental recovery improvements. The literature on public safety governance underscores the need for adaptive capacity, the ability to reallocate resources and innovate operational strategies, in reducing persistent stocks of unresolved cases (Afshar et al., 2025; Albous, 2024; Braga et al., 2018; Cedergren & Hassel, 2024). Without such adaptive capacity, forecasting models will continue to predict slow adjustment rates, as observed in the current study. This critical juxtaposition underscores the need to integrate resource capacity metrics into future modelling to better clarify the drivers of persistence and equilibrium behaviour. It also highlights that time-series persistence, while statistically informative, may mask deeper structural constraints that require policy intervention beyond trend projection.

Finally, an examination of the current results considering the broader literature reveals both opportunities and limitations for future research. Globally, missing persons research has increasingly incorporated mixed-method approaches, combining quantitative forecasting with qualitative insights into reporting behaviour and institutional cultures (Chopin, 2022; Clark,

2016; International Commission on Missing Persons (ICMP), 2021; National Institute of Justice, 2019). Such integrated approaches have proven valuable in identifying latent factors that pure quantitative models might overlook. In contrast, the current study utilises a parsimonious AR(1) framework that prioritises statistical stability in the face of limited data points but may underrepresent nonlinear dynamics and exogenous influences. While the forecasting projections offer useful baseline scenarios, the lack of exogenous predictors, such as socioeconomic variables or policy intervention indicators, limits explanatory power beyond structural persistence. Therefore, future research should aim to incorporate multivariate extensions, including ARIMAX or vector autoregressive models, to capture more complex interrelationships. Additionally, comparative studies across Caribbean states could illuminate region-specific institutional effects on missing persons dynamics. Integrating these broader perspectives would enhance the generalisability and policy relevance of time-series modelling in this domain.

Conclusion

The empirical findings demonstrate that missing persons dynamics in Jamaica exhibit strong structural persistence across missing cases, returned individuals, and persons still missing. Autoregressive coefficients exceeding 0.90 indicate that institutional processes are characterised by inertia, where past system states significantly determine present outcomes. Forecast projections for 2025-2030 suggest gradual convergence toward long-run equilibrium levels under stable structural assumptions. However, the persistence of unresolved cases indicates that backlog accumulation remains embedded within institutional operations. These results reinforce the conceptualisation of missing persons as a dynamic stock variable rather than a static administrative category. The modelling framework confirms that temporal dependence dominates short-run fluctuations while structural forces shape long-run trajectories. Consequently, policy expectations should recognise that meaningful reductions require sustained interventions rather than short-term operational adjustments.

Importantly, the magnitude of persistence observed in this study exceeds that commonly reported in higher-capacity institutional settings, suggesting that structural constraints amplify temporal inertia. This finding implies that improvements in recovery efficiency alone may not significantly alter long-run outcomes unless accompanied by systemic reforms. The equilibrium behaviour identified in the forecasts indicates that the system will adjust slowly toward steady-state levels absent transformative intervention. Therefore, institutional reform must target the underlying mechanisms that generate persistence, including reporting delays, data fragmentation, and coordination inefficiencies. From a governance perspective, these findings provide quantitative evidence that policy impact should be evaluated over extended time horizons rather than annual fluctuations.

Policy Implications

The results carry direct implications for public safety governance and institutional planning in Jamaica. First, the strong autoregressive persistence suggests that policy strategies should prioritise structural capacity building rather than solely increasing operational output. Investments in digital case management systems, integrated data platforms, and real-time

reporting infrastructure would reduce administrative lag and improve case tracking efficiency. International evidence demonstrates that jurisdictions achieving sustained reductions in unresolved cases often rely on technological integration and cross-agency data sharing (Lum & Koper, 2012). Adapting similar frameworks to the Jamaican context could reduce institutional inertia and accelerate case resolution rates.

Second, the forecasting evidence indicates that unresolved cases are likely to accumulate gradually under current dynamics. This pattern suggests that resource allocation must anticipate future workload growth rather than react to short-term increases. Time-series forecasting should therefore be institutionalised as part of annual strategic planning within law enforcement agencies. Because the estimated persistence coefficients are close to unity, policy reforms may take multiple years to generate observable structural change. Decision-makers should incorporate multi-year evaluation frameworks to assess reform effectiveness more accurately. Short-term performance assessments risk underestimating gradual but meaningful institutional improvements.

Third, expanding the analytical model to incorporate socioeconomic predictors, intervention variables, and crime-related indicators would improve forecasting precision and policy relevance. Integrating unemployment rates, demographic shifts, and violence indicators into a multivariate time-series framework would allow policymakers to understand external drivers of missing persons trends. Comparative research across Caribbean states would further clarify whether persistence patterns reflect regional structural characteristics or country-specific institutional constraints. Establishing a continuous monitoring system that periodically updates forecasts would strengthen adaptive governance. Ultimately, reducing long-term unresolved missing cases requires coordinated structural reform, technological modernisation, sustained investment, and ongoing empirical evaluation to disrupt entrenched persistence dynamics.

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